DETECTING THE TYPES OF MULTIPLE SCLEROSIS USING MULTI-LAYER PERCEPTRON WITH HAAR DWT

***Mrs.M.Divya* [1], *Dr.J.Dhilipan* [2] , *Dr A Saravanan* [3]**

[1] *Research Scholar, Department of Computer Applications, SRM IST, Ramapuram Campus, Chennai, Email: divyamathavan3@gmail.com , divyam1@srmist.edu.in*

[2] *Professor & Head, Department of Computer Applications, SRM IST, Ramapuram Campus, Chennai. Email: hod.mca.rmp@srmist.edu.in*

[3] *Professor & Dean Academic, Department of Computer Science and Engineering, Easwari Engineering College, Ramapuram, Chennai, Email: saromanj19@gmail.com*

Abstract

This research work proposes a novel algorithm for detecting the types of multiple sclerosis from brain Magnetic Resonance Images (MRI) using Multi-Layer Perceptron based on Haar Discrete Wavelet Features (DWT) algorithm. The brain images are initially processed with non-linear median filter to reduce the unwanted noise. These pre-processed brain images are fed into the Haar DWT for extracting four different image features in the form of frequency sub bands: High-High (HH), Low-Low (LL), Low-High (LH), and High-Low (HL).Fron this, The LL frequency image features contains all cardinal information's of input data. Further, the LL images alone are processed using MLP for detecting four types of multiple sclerosis, namely clinically isolated syndrome, relapsing- remitting multiple sclerosis, secondary progressive multiple sclerosis and primary progressive multiple sclerosis. The proposed detection algorithm achieves 95% accuracy, 98% dice score, 94% sensitivity and 94% precision, which produces 4% higher accuracy than the existing machine learning based detection methods.

Key Words: Detection, Multiple Sclerosis, Pattern Recognition, Multi-Layer Perceptron, Haar DWT, MRI.

1. INTRODUCTION

Multiple sclerosis (MS) is a type of inflammatory or degenerative disease, which directly affects the central nervous system. It is characterized by the small lesion's presence inside the spinal card or brain of affected patient brain [7].This disease creates communication problem between human brain and other parts of the body and damages the immune cells. The general symptoms of multiple sclerosis in affected patients are loss of power in leg or arm, talking difficulties, depression, loss of vision in an eye, and walking. The sclerosis creates reaction and action problem in the human body. Magnetic resonance imaging (MRI) is an efficient image acquiring tool to diagnose the types of multiple sclerosis, which captures brain tissues with a detailed and very deep structure of the brain without having to use ionization radiation. The symptoms and behaviour of multiple sclerosis affected patients varies based on their types [17]. Mostly the brain tissue contains a complex structure that is interconnected in a complicated manner. There are three different views, like coronal plane, axial plane and sagittal planeare available to detect the lesions types on inner part of brain from MRI images.

The types of multiple sclerosis have been traditionally identified by the expect neuroradiologists based on the lesions colour (White Matter and Gray Matter) and lesions structure. Efficient identification of sclerosis type is essential for clinical assessments and treatment planning. In earlier days, this task used to be performed manually by radiologists. However, manual methods of sclerosis detection are time-consuming and their results often vary among neuroradiologists. So, semi-automatic and automatic detection methods are used for research applications and clinical applications. Existing semi-automatic detection techniques include Support Vector Machine (SVM), K-means, Discrete Wavelet Transformation (DWT), Fuzzy-C-Means (FCM), K-Nearest Neighbor, Continuous Wavelet Transformation (CWT), Conditional Random Field (CRF), Random Forest (RF) and Markov Random Field (MRF) [22]. These methods are less accurate, time-consuming and radiologist dependent process. For this, an automated detection method is required because it reduces the computational load of the human observer. Recently, automated Deep Learning architectures set an exciting trend in multiple sclerosis detection, which represents the complex relationships without having a large number of nodes like KNN and SVM.

For this purpose, an accurate and automated Haar DWT (Discrete Wavelet Transformation) with MLP (Multi-Layer Perceptron) based method for detecting the types of multiple sclerosis is proposed. This proposed method aims to differentiate four types of multiple sclerosis, namely clinically isolated syndrome, relapsing- remitting multiple sclerosis, secondary progressive multiple sclerosis and primary progressive multiple sclerosis. In this, image features are first extracted using Haar DWT and classified using MLP. These classified outputs are compared with the original output for evaluating performance.

The proposed research article is structured as follows: Section 2 discussed the related methods of multiple sclerosis detection methods; Section 3 explains the proposed Multi-layer perceptron with Haar DWT based multiple sclerosis detection methodology; Section 4 discussed the experimental results of the proposed method and Section 5 concludes the paper.

2. RELATED WORKS

The multiple sclerosis is considered anomalous and intracranial cells in the central spinal canal or nucleus of the brain. An accurate and automated identification of the multiple sclerosis from MRI is essential for medical analysis, clinical assessments, interpretation and treatment [17]. There are many techniques are reported for brain sclerosis detection. Recently, K-Means, random forest and FCM methods have been used for multiple sclerosis identification.Mostafa Salem et al. [1] in 2019 and cetin et al. [11] developed a novel clustering-based machine learning algorithms for sclerosis identification. Mostafa Salem et al. [4] in 2018 used some supervised machine learning algorithm for sclerosis detection from T2 weighed lesions. Adi et al. [5] extracted Gray Level Co-occurrence Matrix (GLCM) based features and classified using backpropagation algorithm for performing the sclerosis detection task. Altay et al. [6] classified multiple sclerosis disease activity in MRI.

Eichinger et al. [13] and Finck et al. [14] used MRI images of new born babies for performing the identification task. Schwenkenbecher et al. [16] diagnosis the sclerosis disease in early stage using machine learning approaches. Wolffsohn et al. [17] used new detection strategy for this identification process. These methods need some human interaction to making some classification process. The automated artificial intelligence-based methods are performing this detection task automatically without the human intervention [12]. Han et al. [21] used Generative adversarial network to generate synthetic MRI images. Some others used Convolutional Neural Network algorithms for segmenting and differentiating lesions in multimodal data [18] [19] [20]. Sergi Valverde et al. [3] developed one shot domain adaptation in segmenting multiple sclerosis using CNN.

Recently, automated Deep Learning architectures set an exciting trend in multiple sclerosis detection process. La Rosa et al. [15] segmented cortical and White Matter (WM) lesions in FLAIR and MP2RAGE image sequences of MRI for performing sclerosis identification. Further, the encoder and decoder-based architectures in deep learning becomes popular in an efficient detection of multiple sclerosis[2] [9] [10]. Bengio, Y [8] traineddeep neural network using a novel gradient-based algorithm, which improves the identification process. These deep neural network methods extract patches from input images for performing detection and requires large dataset and higher computation for training a network. To avoid these limitations, the Haar DWT based features have been extractedin MRI data and classified using MLP for an automated detection of multiple sclerosis.

3. PROPOSED METHODOLOGY

The Haar DWT and MLP based multiple sclerosis detection technology have five main phases: Data source; MRI brain image pre-processing; feature extraction using Haar DWT; type of multiple sclerosis detection using MLP and their performance evaluation. The detailed overall workflow of this proposed technique has illustrated in Figure 1 and explained in the following subsections.

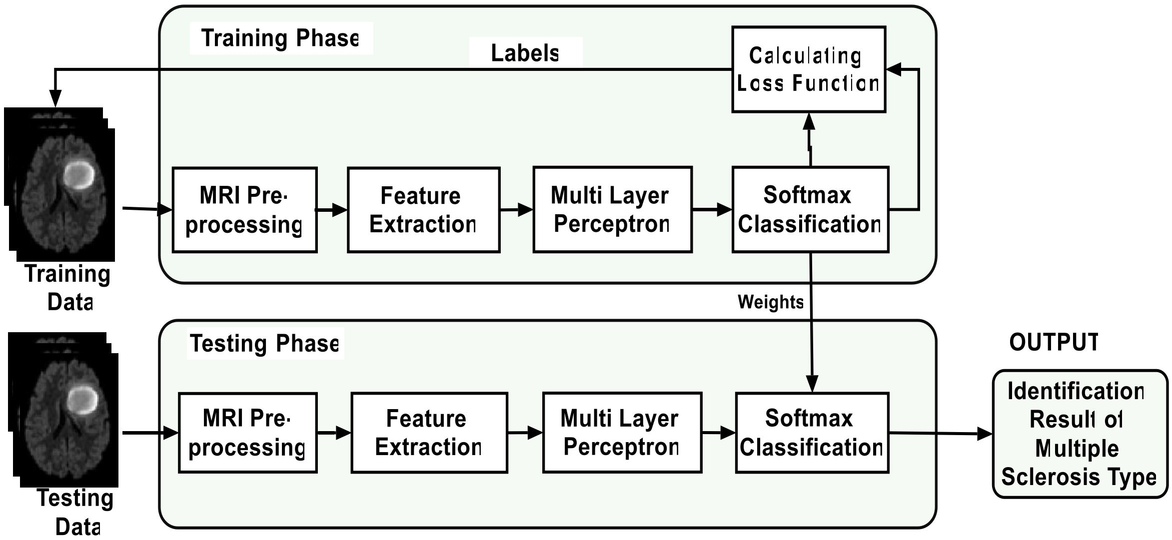

Fig. 1. The proposed Haar DWT with MLP based Multiple Sclerosis detection architecture.

3.1. Data source

The four types of multiple sclerosis data have been collected from various sources of google images. There are 50 images collected in each category of following four types.

- **Clinically Isolated Syndrome (CIS):** Clinically isolated syndrome is somewhat of a "pre-Multiple Sclerosis (MS)" diagnosis. CIS is diagnosed if patients have: A single episode of MS-like symptoms that lasts for 24 hours or longer. Symptoms not related to an infection, fever, or another illness.Symptoms caused by Central Nervous System (CNS) inflammation or demyelination (myelin loss)
- **Relapsing-Remitting MS (RRMS):**Relapsing-remitting MS is the most common type. About 80%–85% of MS cases are initially diagnosed as RRMS .This type features clearly defined attacks (relapses) or new or worsening neurological symptoms separated by remissions—periods of partial or complete recovery.
- **Secondary Progressive MS:**RRMS will eventually transition to this more severe type. Secondary progressive MS gets progressively worse, regardless of remissions. Some people with SPMS continue to have relapses and remissions, but not all do. And the remissions tend to include more symptoms than in RRMS
- **Primary Progressive MS:**A brain lesion typical of MS. Two or more similar lesions in the spinal cord. Evidence of immune system activity in the CNS, including oligoclonal bands and an elevated IgG index.

The detection process of MS varies based on the MS disability, which depends on the stipulated time frame. The time and disability sequence of four MS type is defined in Figure 2.

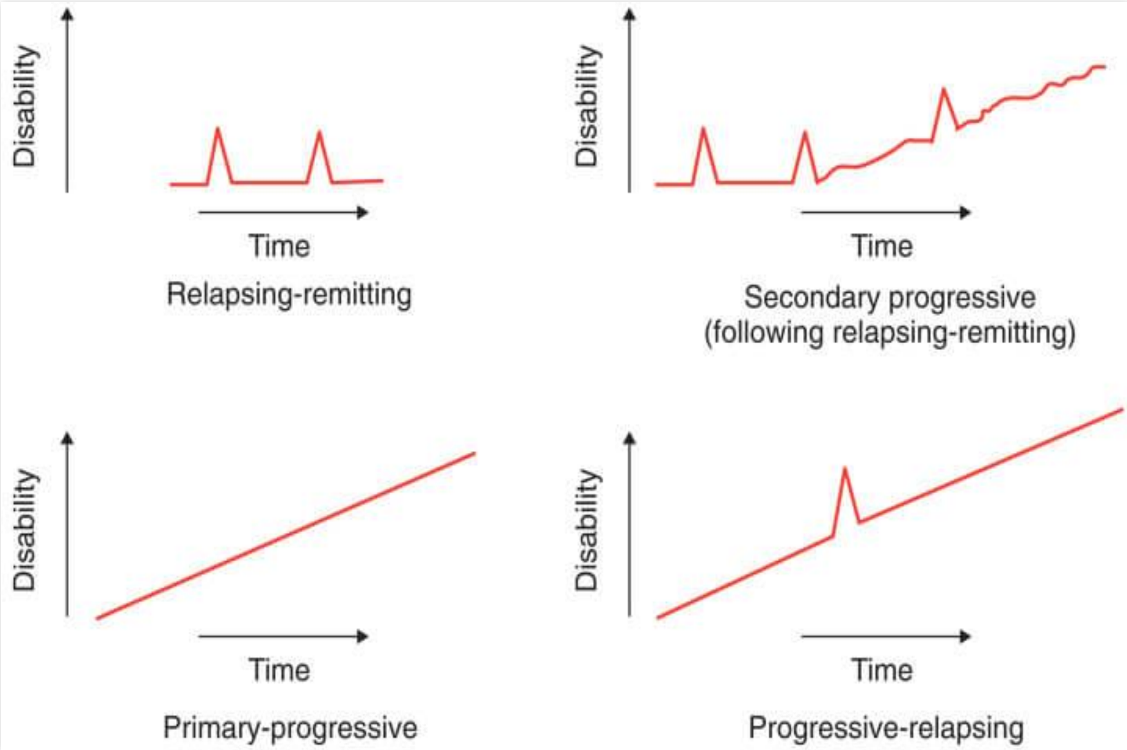

Fig. 2. The disability of multiple sclerosis based on time sequence

3.2. MRI Pre-processing

The most important task in multiple sclerosis detection from brain images is pre-processing. Usually, medical images appear with poor contrast and unwanted noises which requires pre-processing for effective diagnosis. In this research, the median filter is applied in all MRI images for noise reduction and quality improvement. The median filter is a non-linear filter that preserves edge and boundary information while removing noises. In this, each pixel value in an image is replaced by the median value of the neighbourhood window is given in Eq. (1).

$$f(u,v) = median\,\{g[u,v],\ \ (u,v) \in W\} \qquad \dots (1)$$

Where f(u,v) is defines as an output function and w is the pixel values in neighbourhood window.

3.3. Feature Extraction using Haar DWT

The pre-processed images have been feed to the Haar DWT transformation for extracting image features as in the form of frequency sub bands. First, an input image is down sampled using low pass filter and high pass filter to produce low frequency and frequency images respectively [1]. Then these two frequencies are again processed using low pass filter and high pass filter to yield four sub bands: Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH). The Haar DWT feature extraction of an image is illustrated in Figure 3. The LH, HL and HH sub bands are defines as detailed co-efficient and LL sub band is the approximation co-efficient. Here LL sub band holds all significant information is an image, which is used for further sclerosis detection process to detect their types.

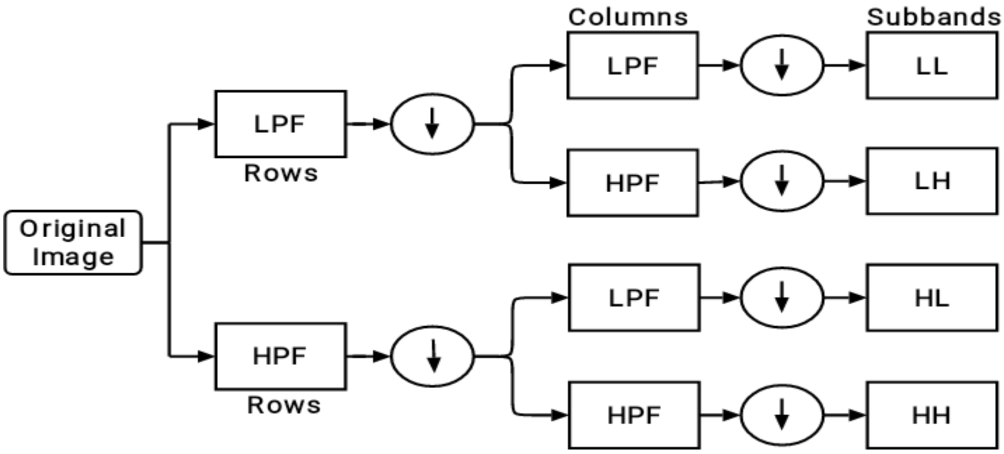

Fig. 3. Architecture of Haar DWT feature extraction.

3.4. Multiple Sclerosis Detection using MLP

The LL sub band features are classified using an MLP algorithm for detecting the types of multiple sclerosis from brain images. The MLP is one of the best training networks for detection based on a forward multi-layer neural network following the delta learning rule. In this, the images have been trainedusing this MLP network for getting a desired outcome. Meanwhile, this algorithm reduced the delta (error) value. The MLP architecture has been is visualized Figure 4. It contains three different layers, namely input layer, hidden layer, and output layer. In this, the input data y ($y_1, y_2 \ldots, y_m$) are combined with bios and network learnable weights w ($w_1, w_2 \ldots, w_m$) to produce the z outcome feature map is given in Eq. (2).

$$z = \sum_{i=1}^{m} w_i \, y_i + bios \qquad \ldots (2)$$

Where, the weights w has been randomly initialized. The featured outcome z is processed by the softmax classification to find the output classified labels. This outcome class labels compared with original to find an error. If it has high error then it can be back propagated to all network neurons and update the intermediate layer weights and bios. Then, all inputs images are processed with these updated weights values. The final updated weights are used to find the type of multiple sclerosis. The performance is evaluated by the comparison between the original output and MLP output.

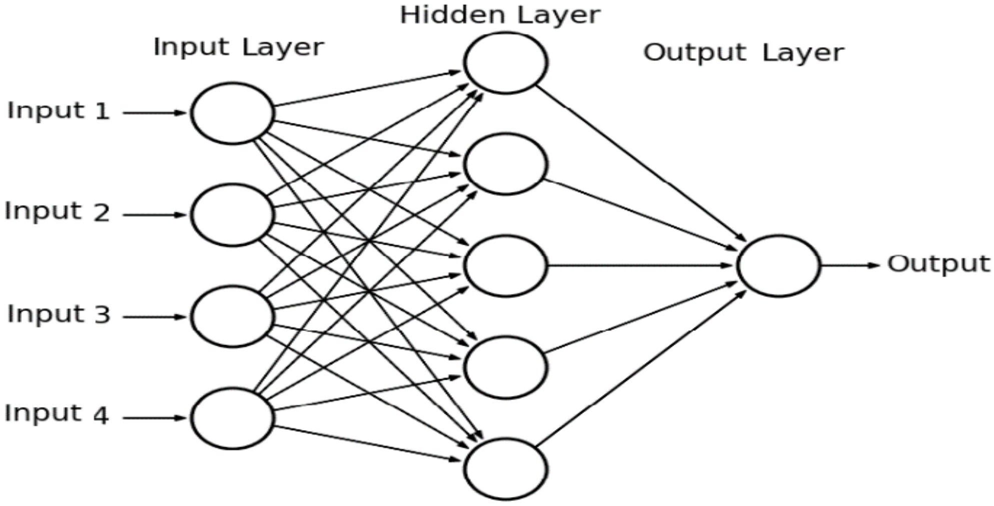

Fig. 4. Architecture of MLP classification.

3.5. Performance Evaluation

The detection performance using Haar DWT and MLP is calculated using Accuracy, Dice score, Sensitivity and Precision are defined in equation (3) - (6).

$$Accu = (TP+TN)/(TP+FP+FN+TN) \quad \ldots (3)$$

$$Dice\ Score = (2TP)/(2TP+FP+FN) \quad \ldots (4)$$

$$Sen = (TP)/(TP+FN) \quad \ldots (5)$$

$$Preci = (TP)/(TP+FP) \quad \ldots (6)$$

where, TP-True Positive (truly detected positive values), TN-True Negative (truly detected positive values), FP-False Positive (falsely detected positive values) and FN-False Negative (falsely detected negative values).

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Effectiveness of Proposed Methodology

This section describes the performance of the proposed method. The effectiveness of the proposed method is tested using 50 images from each multiple sclerosis type. First, all MRI images have been split into testing and training. These images are processed using the median filter to reduce noise and improve quality. Then, image frequency features are extracted using Haar DWT.The LL sub band features are classified using an MLP algorithm for detecting the four types of multiple sclerosis. These outcomes are processed by the softmax classification to find the output classified labels. The performance is evaluated by the comparison between the original output and MLP output by benchmark metrics namely, Accuracy, Dice score, Sensitivity and Precision. The results of the proposed multiple sclerosis detection method are defined in Table 1. The proposed method results are compared with the acquired results of state-of-art automated detection methods like Extreme Learning Machine (ELM), Ensemble Classifier (EC) and Feed Forward Artificial Neural Network (FFANN) are detailed in Table 2 and Figure 5.

Table 1: Performance of proposed multiple sclerosis detection method.

BRATS 2018 dataset				
Sequence Name	**Accuracy**	**Dice Score**	**Sensitivity**	**Precision**
HGG	0.94	0.95	0.94	0.95
LGG	0.96	0.95	0.94	0.95
Average	**0.95**	**0.95**	**0.94**	**0.94**

Table 2: Performance comparison of proposed multiple sclerosis detection method.

Classification Technique	Accuracy (%)	Dice Score (%)	Sensitivity (%)	Precision(%)
Extreme Learning Machine (ELM)	86.00	91.63	93.12	90.20
Ensemble Classifier (EC)	91.17	94.81	93.47	92.17
FFANN	84.33	90.66	91.94	89.41
Proposed Method	**95.00**	**97.00**	**94.00**	**94.00**

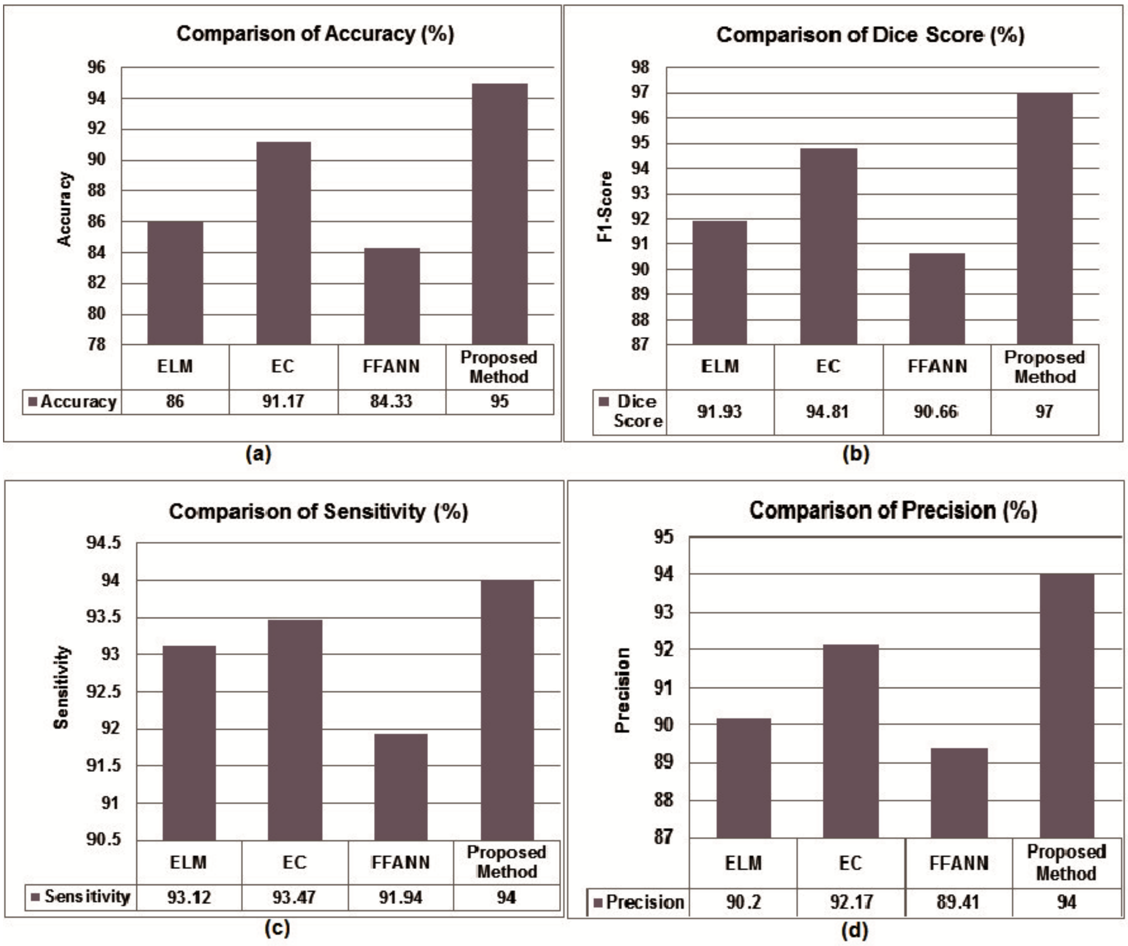

Fig. 5. Performance comparison of proposed multiple sclerosis detection method.

It’s very clear from Table 2 and Figure 5 has significant improvements in four parameters: accuracy of the proposed method is 95% whereas ELM, EC and FFANN method have an accuracy of 86%,91.17 % and 84.33 % respectively; dice score of the proposed method is 97% whereas ELM, EC and FFANN method have a dice score of 91.63 %, 94.81 % and 90.66 % respectively; sensitivity of the proposed method is 94% whereas ELM, EC and FFANN method have sensitivity value of 93.12 %, 93.47 % and 91.94 % respectively; precision of the proposed method is 94 % whereas ELM, EC and FFANN method have a precision value of 90.20 %, 92.17 % and 89.41 % respectively. From these results, the proposed Haar DWT and MLP based method have 4% higher accuracy than the automated detection methods.

5. Conclusion

Accurate detection of multiple sclerosis type from MRI is essential for clinical assessments. Existing multiple sclerosis detection methods need user interaction from the human observer which has less accuracy and time-consuming process. For this purpose, an accurate and automated Haar DWT (Discrete Wavelet Transformation) with MLP (Multi-Layer Perceptron) based sclerosis type identification method is proposed to differentiate the four types of multiple sclerosis, namely clinically isolated syndrome, relapsing- remitting multiple sclerosis, secondary progressive multiple sclerosis and primary progressive multiple sclerosis. In this, image features are extracted using Haar DWT and classified using MLP. These classified outputs are compared with the original output for evaluating performance. The effectiveness of this proposed method is tested using the collected google images, which achieves 4% higher accuracy than the existing state-of-art detection methods.

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